Brightness Preserving Image Contrast Enhancement Using Weighted Mixture of Global and Local Transformation Functions

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Abstract: *Transformation functions utilizing the global information content of an input image have been long serving contrast enhancement by stretching the dynamic range of intensity levels. Other transformation functions focus on local information content to correct image details, such as edges and texture. In this paper, an effective method for image contrast enhancement is presented with a mapping function, which is a mixture of global and local transformation functions that improve both the brightness and fine details of the input image. The final mapping function incorporates a local intensity-pair distribution generated expansion function from each image block to control the enhancement of image details that the global transformation function alone may fail to improve. Contribution from the global transformation function preserves the overall image brightness and contrast stretching. Experiments show that the proposed method competes well with the existing enhancement methods, both subjectively and quantitatively.*

Keywords: *Contrast enhancement, global transformation function, local transformation function, and intensity pair.*

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1. Introduction

Image contrast enhancement is a classical problem in image processing and computer vision. The enhancement is widely used for medical image processing and as a preprocessing step in speech recognition, texture synthesis, and many other image/video processing applications [13, 14, 18, 20]. Existing enhancement approaches fall into two broad categories: spatial domain methods and frequency domain methods [6]. The spatial domain techniques have gained more popularity as they are based on direct manipulation of pixels in an image and are straightforward for visualizing the effect. In the last few decades, myriad spatial domain methods have been developed for this purpose. Some of these methods make use of simple linear/non-linear intensity level transformation functions [6] whereas others use complex analysis of different image features such as the edge [1] and connected component information [2].

A very popular technique for contrast enhancement of images is Histogram Equalization (HE) [6], which is simple and has good performance compared to nearly all types of images. HE performs its operation by remapping the intensity levels of the image based on the probability distribution of the input intensities [3]. Various researches have been performed on HE, and many methods have already been proposed. Generally, these methods are classified into two principle categories; global and local HE [9]. Global HE (GHE) uses the histogram information of the entire input image for its transformation function [6, 15]. Though this global approach is suitable for overall enhancement, it fails to adapt the local brightness features of the input image and shifts the mean intensity to the middle intensity level, regardless of the input mean intensity [3, 9, 10]. Thus it appears to be inappropriate for consumer electronic products. Local HE (LHE) can remove the local brightness problem [6], however the overlapping sliding mask mechanism makes the LHE computationally expensive. With the technological advancements in processing power, the speed is no longer a problem. The LHE still faces difficulty with amplified noise and an unnatural output due to over-enhancement. Another approach is to apply a partially-overlapped or non-overlapped block based HE [9]. Nonetheless, most of the time, these methods produce undesirable checkerboard effects on enhanced images [6, 9].

Some researchers have focused on the improvement of HE by partitioning the histogram into several parts and equalizing them separately. Bi-HE (BHE) divides the input image histogram into two parts based on the histogram's mean [10, 15]. The Dualistic Sub-Image HE (DSIHE) exploits the median of the input histogram [22]. The dominant trait of DSIHE is that it is better in preserving an image's brightness and entropy [7, 22]. Chen and Ramli proposed Minimum Mean Brightness Error Bi-HE (MMBEBHE) in [5], an extension of the BBHE method to optimally maintain the mean brightness [7]. Unlike BBHE, the partitioning point in the histogram is the intensity that produces the minimum difference between the mean intensity of the output and input image. One shortcoming of MMBEBHE is that the method has to check for all possible partitioning values from *0* to *L-1*. Though these methods can perform better brightness enhancements than GHE, they also cause more significant side effects depending on the variation of intensity distribution in the histogram [17] and degraded visualization as it loses the natural look [15].

Recursive Mean-Separate HE (RMSHE) is another improvement of BBHE, which recursively splits each new histogram based on their respective mean and equalizes them independently [3]. Chen and Ramli mathematically derived that RMSHE has good brightness preservation. Sim *et al*. [16] shares similar concepts with DSIHE and RMSHE. The proposed technique, known as Recursive Sub-Image HE (RSIHE), iteratively divides the histogram based on median rather than mean values. Since the median value is used, each partition shares the same number of pixels. Therefore, both RMSHE and RSIHE divide the histogram into 2^r number of partitions and they preserve the brightness to better extend than previous partitioning method to enhance the visual outlook. However, finding the optimal value of r is difficult, and with a large value of r there will be no enhancement, despite the fact that the brightness preservation property is fulfilled adequately [7, 15, 21].

All the methods described above exhibit the same weakness of only dividing the histogram into multiplications of two, where the recursion value r determines the number of partitions, i.e., 2^r sections of sub-histograms. An alternative appeared by partitioning the histogram into arbitrary sub-histograms based on the shape of the histogram. Multi-HE (MHE) [11], Brightness Preserving Dynamic HE (BPDHE) [7], and Brightness Preserving Weight Clustering HE (BPWCHE) [15] used this partitioning strategy. MHE uses the Otsu threshold selection technique to determine the optimal number of histograms from all possible sub-histograms to minimize certain discrepancy functions. By varying the discrepancy function, Menotti *et al.* in [11] have presented Minimum Within-Class Variance MHE (MWCVMHE) and Minimum Middle Level Squared Error MHE (MMLSEMHE) to perform less intensive image contrast enhancement with a more natural look. Since MHE is rather computationally expensive for estimating the optimal number of sub-histograms, Brightness Preserving Dynamic HE (BPDHE) was used to partition the histogram at local [7]. BPDHE is an expansion of Dynamic HE (DHE) [19] that normalizes the output intensity by bringing the mean intensity close to the mean intensity of the input image. Both BPDHE and DHE map the sub-histograms into a new dynamic range before performing the classical HE. This new dynamic range is a function of the span of each sub-histogram. Some researchers have opted to choose the local minima instead of the local maxima [19]. Generally, within the histogram shape, there are too many maxima or minima points, and the histogram is partitioned into too many sub-histograms that ultimately end in an insignificant amount of improvement. In the BPWCHE method, the authors have proposed to cluster non-zero histogram bins to unique clusters based on three criteria [15]. Though the recent algorithms divide the histogram based on a different principle, their enhanced output images do not differ much in terms of the visual quality.

Most of the HE techniques use global information. Occasionally, information from some small image region is used; however none of them consider the spatial relationship among the pixel intensities in the image. Jen *et al.* [8] focused on the local information of the image content. The authors have used the distribution of intensity-pairs to consider this spatial relationship for contrast improvement. Instead of the histogram of intensities, the method presented in [8] has constructed a global transformation function based on the histogram of the intensity-pairs. However, the resultant mapping function still suffers from undesired drawbacks, such as the loss of tiny details and texture information.

The existing global transformation function fails to take care of structural details in the image. As a result, loss of tiny details and/or enhancements of noise are observed. Alternatively, the local transformation function provides more attention to the structural details of a small region, overlooking the global impact. Thus, in our proposed method, the global transformation function is combined with the local intensity-pair distribution generated expansion function. This mixture function allows us to avail the advantages of the global HE technique, concurrently preserving the fine details of the image utilizing the spatial relationship information of neighboring pixels. Since the local transformation function will change the mean brightness, we have opted to normalize the intensity value to bring the mean brightness closer to the input mean brightness, thus, preserving the brightness preservation property.

The rest of the paper is organized as follows. The proposed method is described in section 2. Section 3 presents experimental results with both subjective and quantitative evaluation to illustrate the performance of the proposed idea, and section 4 concludes this paper.

2. Proposed Algorithm Description

2.1. Global Transformation Function

The global transformation function remaps the intensity values of the image in such a way that it stretches the dynamic range of the image histogram, resulting in overall contrast enhancement. The Recursive Mean-Separate HE (RMSHE) is used as a generalization of both GHE and BBHE that allows scalable brightness preservation.

The main idea is to divide the input histogram into two parts based on the mean of the input histogram. After mean-partitioning, the resulting sub-histogram pieces might be further divided into more sub-histograms based on their respective means depending on the level of recursion, *r*. The resulting 2^r histogram regions are equalized independently. Thus, the global transformation function is obtained as

$$T(g) = g_{\min} + (g_{\max} - g_{\min}) \times \frac{\sum_{x=g_{\min}}^{g} h(x)}{\sum_{x=g_{\min}}^{g_{\max}} h(x)}. \quad (1)$$

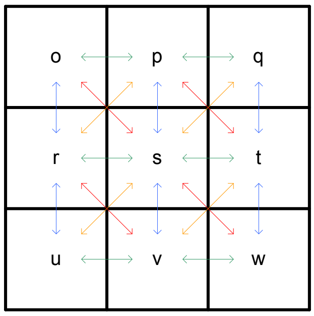
where g denotes the intensity value, $g_{\min}$ and $g_{\max}$ are the lower and upper bound of each histogram partition, *h(x)* denotes the histogram count for intensity value *x*, and *T(g)* is the global transformation function. The level of recursion provides scalability to allow adjustment of the brightness level, based on individual's preference. The transformation function in equation 1 changes the input mean intensity μ_i to the output mean intensity μ_r as shown in equation 2.

$$\begin{aligned} r &= 0, & \mu_r &= \mu_c \text{ where, } \mu_c = (g_0 - g_{L-1})/2 \\ r &= 1, & \mu_r &= (\mu_i + \mu_c)/2 \\ r &= 2, & \mu_r &= (3\mu_i + \mu_c)/2 \\ &\dots \\ r &= n, & \mu_r &= ((2^n - 1)\mu_i + \mu_c)/2. \end{aligned} \quad (2)$$

A more detailed explanation of equation 2 can be found in [3].

2.2. Local Expansion Function from Intensity-Pair Distribution

The intensity-pair distribution based method exploits the neighborhood information of all pixels to generate a global intensity mapping function [8]. Generally, digital images contain a 2D array of intensity values, with locally varying statistics that results from a different combination of abrupt features such as edges and homogeneous regions [6]. Since different parts of the image have different statistical characteristics, we apply the same approach block-wise to handle local information more effectively. Within each block, we generate the set of intensity pairs $\{(a_1,b_1),(a_2,b_2),\dots,(a_j,b_j),\dots,(a_m,b_m)\}$ from a pixel's 8-connected neighbors. Figure 1 shows the intensity pairs from a sample 3×3 neighborhood window.



(a)

$$\left\{\begin{matrix} (o,p), (p,q), (o,r), (p,r), (r,s), \\ (o,s), (p,s), (q,s), (s,t), (p,t), \\ (q,t), (r,u), (s,u), (u,v), (r,v), \\ (s,v), (t,v), (v,w), (s,w), (t,w) \end{matrix}\right\} \equiv \left\{\begin{matrix} (a_1,b_1), (a_2,b_2), \\ \dots,(a_j,b_j), \\ \dots,(a_m,b_m) \end{matrix}\right\}$$

(b)

Figure 1. A set of intensity-pairs from a 3×3 neighborhood window. Each arrow indicates a pair from two intensity values. The elements in each pair are order independent.

All of the pairs (a_j,b_j) do not come from edge regions. Thus, the difference between a_j and b_j defines which pairs belong to smooth or edge regions. A smooth region is usually perceived by human beings as an area of uniform intensity. Though these regions are thought to be homogenous, there are some minor variations in the intensity values, which are undetected by the human eye. The Weber ratio κ characterizes the minimum change in intensity ΔI discriminable with respect to the original intensity I. This ratio is not a constant, but rather nonlinear as a function of illumination [6]. Some psychologists referred to a κ value of 7.9% for detection of a change in brightness that is noticeable to human perception [12]. Depending on the intensity difference within a pair exceeding a certain threshold, ΔI=7.9 ≈8, either a train of expansion forces or a train of anti-expansion forces is generated between the intensity range "a_j to b_j" of that pair.

In a real 2D image, many edge-pairs exist near the edges. Therefore, we accumulate all the expansion forces between the edge pairs. Now the smooth intensity pairs may lie within the intensity range of the edge pairs. Due to the contrast stretch, the smooth region's intensity will also be stretched. To avoid such circumstances, anti-expansion forces are generated within the intensity range of the smooth intensity pairs. Similarly, all the anti-expansion forces are accumulated for those intensity pairs of the smooth region, and then subtracted from the expansion forces with a certain impact factor *w* to obtain the net-expansion force. The anti-expansion force ensures the smoothness for homogeneous regions in net-expansion force.

The net-expansion force, *F* is obtained in equation 5:

$$F_{+}(x) = F(x) + 1 \quad \forall x \in [a_j, b_j] \qquad if\left|a_j - b_j\right| \geq \Delta I. \tag{3}$$

$$F_{-}(x) = F(x) - 1 \quad \forall x \in [a_j, b_j] \qquad if\left|a_j - b_j\right| < \Delta I. \tag{4}$$

$$F = F_{+} - w \times F_{-}. \tag{5}$$

where F_+ is the expansion force, F_- is the anti-expansion force, and w is set as suggested in [8]. Finally, the expansion forces are accumulated using equation 6 and normalized to determine the local expansion function from the intensity-pair distribution.

$$G(g) = g + \sum_{g_{\min}}^{g} F(x). \tag{6}$$

2.3. Mixed Intensity Mapping Function

In our proposed method, the key objective is to identify subtle details while maintaining local and global image enhancement. The block-based approach allows us to move the sliding block throughout the whole image, and for each block position we get an expansion function from the intensity-pair distribution. To generate the final intensity mapping function for the block's center pixel, a weighted sum of the expansion function and the global transformation function is computed by equation 7

$$M(g) = k \times G(g) + (1-k) \times T(g)\,. \tag{7}$$

where k is the weight value within [0.0, 1.0].

2.4. Brightness Normalization

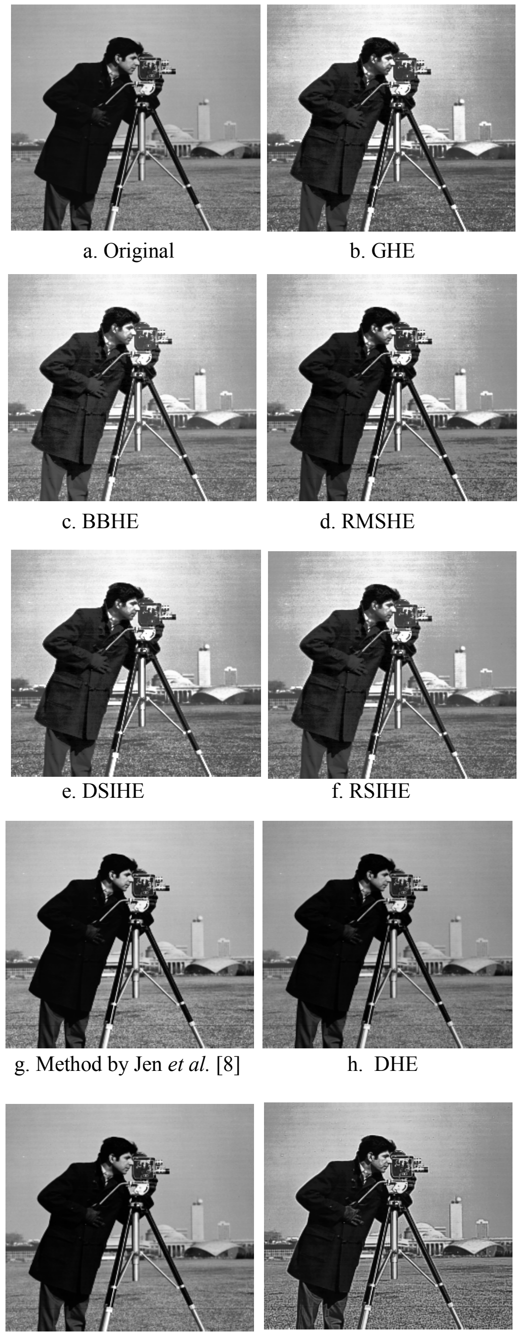
The local transformation function in the final mapping function $M(.)$ causes the output mean value to shift far away from μ_r, and thus deviates from preserving the input mean brightness. Thus, an additional brightness normalization step is performed on the transformed image by equation 8

$$o(x,y) = {\mu_i}\big/{\mu_t} \times t(x,y). \tag{8}$$

where $t(x,y) = M(s(x,y))$ is the transformed image after applying the mixed mapping function on the source image $s(x,y)$, $o(x,y)$ denotes the output image, and μ_t is the mean intensity value of $t(x,y)$. As the mixed function has already considered the enhancement of local details, the final brightness normalizing function only shifts the intensity values to adjust the output mean μ_o closer to the earlier input mean μ_i. The purpose of equation 8 is to compensate for the brightness deviation caused by the impact of local transformation.

3. Results and Discussion

In this section we have demonstrated the subjective and quantitative enhancement performance of our proposed method in comparison with eight existing enhancement algorithms: GHE, BBHE, RMSHE, DSIHE, RSIHE, the method presented in [8], DHE, and BPDHE. For both RMSHE and RSIHE, the parameter value of r has been fixed to two, and for the method in [8] the parameters are set to (m, g, k) = (2.0, 0.1, 0.5). With these parameter values, the enhanced outputs are illustrated in Figures 2, 3, and 4.



a. Original b. GHE c. BBHE d. RMSHE e. DSIHE f. RSIHE g. Method by Jen *et al.* [8] h. DHE i. BPDHE j. Proposed method

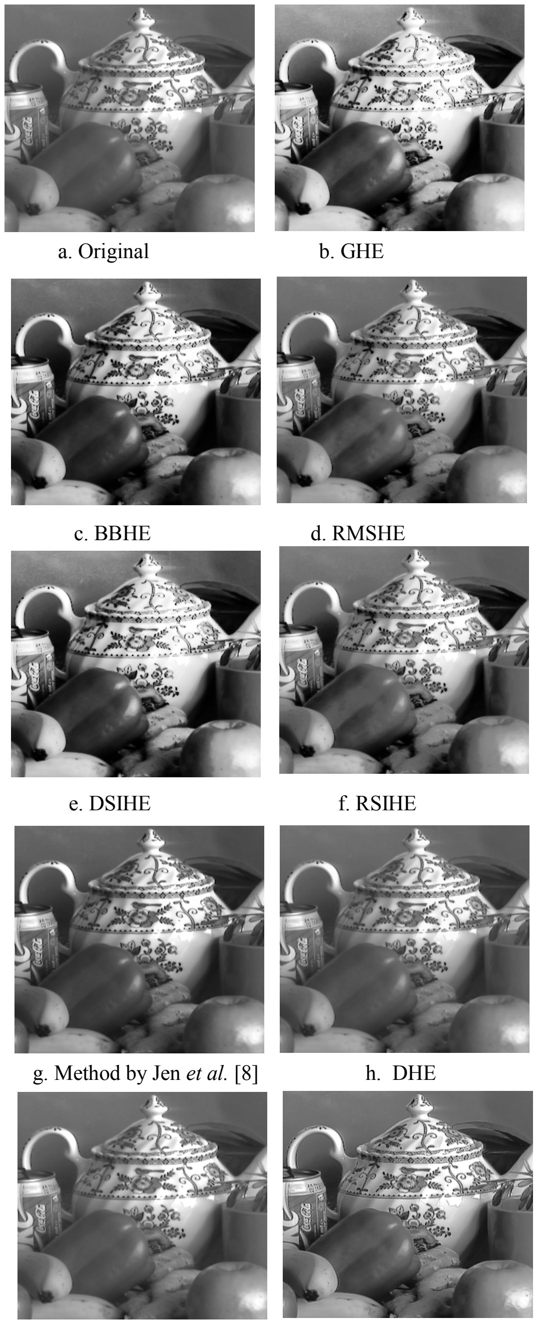
Figure 2. Comparison results. (b-i) by existing methods.

The enhanced output of our proposed method is shown with a parameter set of (r, k) = (2, 0.5) and considering the neighborhood information from a 3×3 local window. Though more variations can be achieved by varying the parameter values, we preferred to show the outputs with the same values that are used for other existing methods. Thus, consistency with RMSHE (i.e., $r = 2$) and the method in [8] (i.e., $k = 0.5$) are maintained.

The proposed method is built through three main steps. It first scans the input image in order to analyze the histogram, and builds the global transformation function based on the concept presented in section 2.1. Next, the global transformation function is handed over to a sliding window based approach which generates the final transformation functions. At each pixel position, the expansion function is generated from the region defined by the neighborhood window. This expansion function provides data about the local texture and adjusts the global transformation function towards the final mapping function that now contains some neighborhood information. Therefore, each pixel position has its own intensity mapping function and generates the corresponding out value. Finally, the brightness normalization step is performed to produce the enhanced image with more brightness preservation.

We have used several test images to evaluate our proposed method and compared the effectiveness in terms of subjective and objective measures. Based on the contrast enhancement and visual satisfaction, the proposed method has excellent enhancement. In Figure 2, the method in [8], DHE, and BPDHE failed to increase the contrast of both the cameraman and corresponding camera. Though the other methods have increased details of the cameraman's coat, they failed to preserve a natural look of the image. Moreover, the texture on the camera device wasn't enhanced by any of the methods, but rather introduced artifacts and a washed out effect. On the contrary, our enhanced output shows good enhancement on the cameraman, his camera and its background, with a more natural look and sharpness. The background appears less blurry than the background generated by existing methods.

The strength of our algorithms can be shown more with the 'teapot' image, as shown in Figure 3. In this image, the left and right side of the teapot are hazy compared to the center body since they are out of focus. While the contrast was stretched by GHE, BBHE, and DSIHE, there was a significant washed-out effect. Other approaches preserved the natural look but failed to reduce the haziness effect due to the lack of local information and actions. Our method has imposed significant sharpness at either side. In the output image shown in Figure 3 (j), a natural looking sharp image with enough overall brightness and local details is observed. Another set of test outputs is shown in Figure 4 with the 'satellite' image. Except for DHE, BPDHE, and the method in [8], the other methods have an over-exposure effect in the bright regions. Though these three existing methods are free from over-saturation, they could not enhance the structural details in the upper portion of the image. Figure 4 (j) shows the benefits of applying the proposed method as the enhanced image contains more sharp edges.



a. Original b. GHE

c. BBHE d. RMSHE

e. DSIHE f. RSIHE

g. Method by Jen *et al.* [8] h. DHE

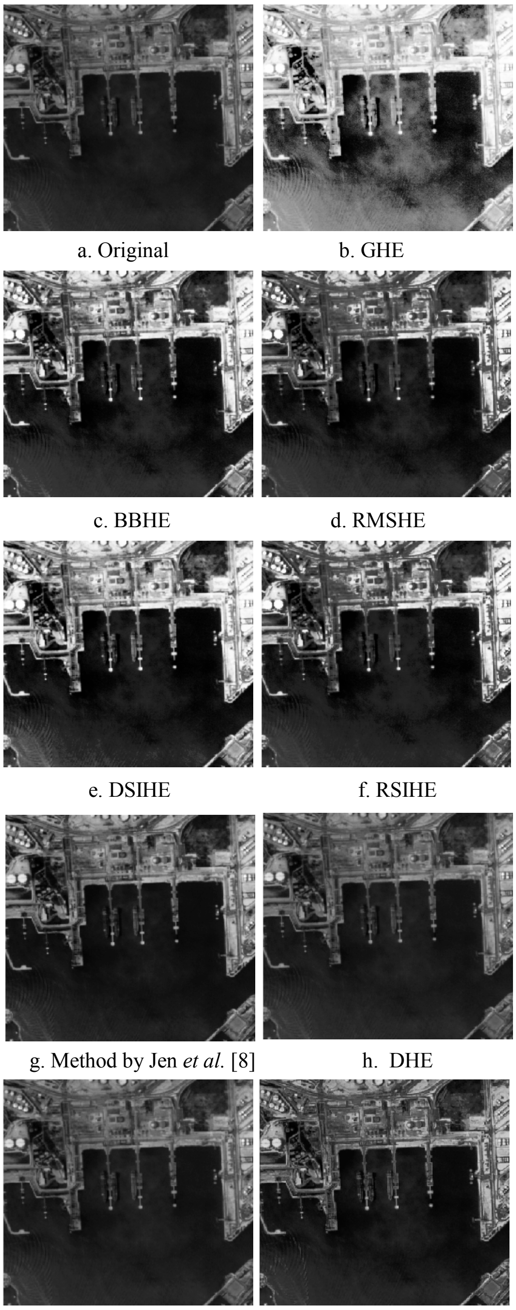
i. BPDHE j. Proposed method

Figure 3. Comparison results (b-i) by existing methods.

The Absolute Mean Brightness Error (AMBE) in equation 9 indicates how close the output mean is compares to the input mean intensity [5, 15]. This objective measurement is defined to rate the performance in preserving the original brightness.

$$AMBE = \left| \mu_o - \mu_i \right|. \tag{9}$$

A smaller value of AMBE indicates a better preservation of the brightness property. Table 1 lists all of the AMBE values for the three test images: 'cameraman', 'teapot', and 'satellite'. Table 1 shows that the proposed method has maintained an output mean very similar to the input mean intensity. The performance is competitive with the recent BPDHE method, with less undesirable artefacts.



a. Original b. GHE
c. BBHE d. RMSHE
e. DSIHE f. RSIHE
g. Method by Jen *et al.* [8] h. DHE
i. BPDHE j. Proposed method

Figure 4. Comparison results. (b-i) by existing methods.

Table 1. AMBE.

Method	Test Image		
	Cameraman	Teapot	Satellite
GHE	10.089	13.086	72.186
BBHE	24.158	11.719	20.733
RMSHE	12.449	5.961	6.84
DSIHE	17.903	0.419	24.81
RSIHE	9.477	2.041	11.281
by Jen *et al.* [8]	9.418	12.428	1.429
DHE	6.999	2.999	0.731
BPDHE	0.002	0.025	0.151
Proposed	0.014	0.074	0.003

Table 2. AAMBE.

Method	AAMBE
GHE	72.663
BBHE	17.881
RMSHE	5.199
DSIHE	17.296
RSIHE	6.257
by Jen et al. [8]	6.828
DHE	1.922
BPDHE	0.063
Proposed	0.210

In order to examine whether the proposed method maintains the AMBE for other images, we have used another similar measure known as the Average AMBE (AAMBE) [7], which is defined in equation 10.

$$AAMBE = \frac{1}{N}\sum_{i=1}^{N} \left|\mu_o - \mu_i\right| \qquad (10)$$

where N is the number of test images. Table 2 lists the respective AAMBE values for GHE, BBHE, RMSHE, DSIHE, RSIHE, the method in [8], DHE, BPDHE, and the proposed method. From Table 2, it is evident that our proposed method is capable of preserving the brightness to a higher degree with respect to most of the existing methods.

4. Conclusions

The strength of our approach lies in the interpolation of two transformation functions: global and local functions from the intensity-pair distribution of each neighbourhood region. Here this mixture function enhances the overall contrast and fine details that the global function missed. The presented method can produce natural looking images with more sharpness while preserving brightness closer to the input image without introducing any artefacts. In this paper, the output in the experimental results and the data in the objective evaluation based on AAMBE show that the enhanced images have a promising visual quality for display purpose in consumer electronic products.

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